Patterns and determinants of inventors' mobility across European urban areas

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Highly skilled professionals are regarded as one of the main driver for the economic development of cities through their effect on innovative capabilities. Skilled individuals are mobile in space and tend to cluster within a limited number of urban areas, therefore a crucial question is what factors shape this flows and influence the divergent levels of economic development across urban areas. Building on these considerations, this paper takes advantage of a large-scale dataset to shed light on the patterns and determinants of inventors' mobility across European urban areas. First, a descriptive analysis is carried out to document the dynamics of inventors' mobility and their spatial dimension. Second, a gravity model is used to analyse how job opportunities and socio-professional networks influence the flows of inventors between urban areas. From a methodological perspective, this paper uses a spatial filtering variant of the Poisson gravity model, which accommodate the nature of the data, while controlling for multilateral resistance and spatial autocorrelation in mobility flows. The descriptive analysis suggest that inventors' mobility occurs primarily between relatively large and collocated urban areas, partly because of the high level of circular and intra-firm mobility. The econometric analysis shows that employment opportunities, social networks, as well as various forms of proximity are important determinants of inventors' mobility.

Keywords:
Inventors' mobility, urban areas, job opportunities, socio-professional network, Poisson gravity model, spatial filtering

JEL codes:
J61, O18, O31,O33

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Abstract Highly skilled professionals are regarded as one of the main driver for the economic development of cities through their effect on innovative capabilities. Skilled individuals are mobile in space and tend to cluster within a limited number of urban areas, therefore a crucial question is what factors shape this flows and influence the divergent levels of economic development across urban areas. Building on these considerations, this paper takes advantage of a large-scale dataset to shed light on the patterns and determinants of inventors' mobility across European urban areas. First, a descriptive analysis is carried out to document the dynamics of inventors' mobility and their spatial dimension. Second, a gravity model is used to analyse how job opportunities and socio-professional networks influence the flows of inventors between urban areas. From a methodological perspective, this paper uses a spatial filtering variant of the Poisson gravity model, which accommodate the nature of the data, while controlling for multilateral resistance and spatial autocorrelation in mobility flows. The descriptive analysis suggest that inventors' mobility occurs primarily between relatively large and collocated urban areas, partly because of the high level of circular and intra-firm mobility. The econometric analysis shows that employment opportunities, social networks, as well as various forms of proximity are important determinants of inventors' mobility.

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1 Introduction

It is in large cities where vast majority of substantial innovations emerge. In an influential contribution, Jaffe et al. (1993) showed that during the 1980s, 92% of all USPTO patents were granted to inventors residing in metropolitan areas, while only three quarters of the population resided in these areas. These results are consistent with Audretsch and Feldman (1999) who report that in 1982 in the United States, less than 4% of the product innovations took place outside of metropolitan areas and that half of the new innovations occurred in just four metropolitan areas. Jacobs (1969) long ago pointed to the importance of cities as a source of innovative change. She argues that the diversity of people, firms and cultures in large urban areas constitute a fertile ground for novel ideas and innovations. As cities may provide the meeting point for people from different backgrounds, culturally diverse cities may help innovation. The connection with economic theory is provided by Lucas (1988) who introduced skills and knowledge in a neoclassical growth model. In his setting, productivity gains are associated with the clustering of skilled people within urban areas. Although Lucas' model did not give any indication about the actual mechanisms by which such externalities occurred in the real world, Lucas recognized that "the scope of such effects must have to do with the ways various groups of people interact" (1988, p.37). From an empirical perspective, Glaeser (1999) argues that knowledge flows faster in cities because the higher concentration of individuals provides numerous opportunities for interactions and the cost of communication is lower. As a consequence, larger and more skilled urban areas are found to be more productive (Glaeser et al., 2004), more innovative and tend to growth faster (Carlino et al., 2007; Bettencourt et al., 2007). In this regard, Glaeser and Resseger (2010) highlight strong complementaries between knowledge and agglomeration, so that knowledge externalities amplify the benefits of agglomeration while agglomeration facilitates the accumulation of knowledge.

Such circular-causation mechanisms are at the root of new economic geography and growth models, which explain the distribution of innovative activity through the interplay of diverse agglomeration and dispersion forces. Specifically, these models combine Krugman (1991)'s core-periphery model and endogenous growth models along the lines of Romer (1990) and Grossman and Helpman (1991), while allowing for labour mobility (Black and Henderson, 1999; Baldwin and Forslid, 2000). These models highlight the importance of knowledge externalities and their spatial dimension in determining both the productivity and the location of innovative activity. Depending on the range of knowledge externalities, a core–periphery pattern can emerge as firms and skilled workers cluster within urban areas. As such cities become more attractive, further concentration of firms and factors occurs, pushing these cities' capacity to innovate and grow at the expense of peripheral areas. One could also observe a counteracting effect whereby firms in the periphery also benefit from innovations in the core (Fujita and Thisse, 2002). A shortcoming to these models is that they do not account for the actual mechanisms through which knowledge diffuses in space. The empirical geography of innovation literature have established that the mobility of skilled individuals both in space and across organizations constitutes an important mechanism of embodied knowledge transfer. Central to this reasoning is the idea that skilled workers on the move can transfer embodied knowledge from their initial workplace to the new one (Almeida and Kogut, 1999), and conversely channel back the knowledge they acquired thanks to the link they have kept with their previous environment (Agrawal et al., 2006). Besides, firms hiring skilled workers are not only more likely to innovate, they are also able to build an absorptive capacity in order to capture and use productively external knowledge (Massard and Mehier, 2009). To the extent that knowledge diffuses according to the mobility patterns of skilled individuals, this should lead to an increased relevance of mobility choices on the spatial distribution of innovative activity.

While there is large consensus on the importance of talented individuals on the distribution of innovation, far less attention has been devoted to the factors driving their location decisions. In fact, skilled workers is a mobile factor that relocate in space. There is considerable theory and evidence showing that people endowed with human capital are more likely to relocate from one place to another, since they are both more adaptable to different jobs and better able to take advantage of the opportunities offered by a different location. Understanding their mobility choices is an important issue given their disproportionate contribution to innovative performance, their increasing level of mobility and their tendency to cluster within a restricted number of urban areas. This paper focuses on inventors, which represent a specific category of skilled workers. Arguably, inventors constitute a highly representative sample, since they are directly involved in the production of new knowledge and therefore, have a large impact on the diffusion of knowledge across cities. Existing evidence on the determinants of inventors' mobility in Europe adopt a fairly microeconomic perspective of focus on a restricted category of inventors. Lenzi (2009) explores the mobility patterns for a group of Italian inventors in the pharmaceutical sector using survey and patent data. Crespi et al. (2007) analyses the mobility of inventors from academia to private firms for six European countries. Finally, Miguelez and Moreno (2014) adopt a more macroeconomic approach to investigate what drives inventors' mobility across regions. This paper contributes to the empirical literature in at least three ways. First, this paper takes advantage of a large-scale dataset to shed light on the patterns of inventors' mobility across European urban areas, and their spatial dimension. To my knowledge, such a categorisation of mobility does not exist at the for Europe, especially at the urban level, which represent a highly relevant spatial scale of analysis.

Building on these results, a gravity model is used to analyse more formally how job opportunities, and socio-professional networks influence the flows of inventors between urban areas. This focus is motivated by the role of employment opportunities in workers' location choices in the theoretical literature introduced above. Besides, while both skilled mobility and professional networks have been shown to influence the geography on innovation, they have often been investigated separately. However, such a distinction would be welcome since mobility may influence the structure of networks by creating new or bridging existing networks (Miguelez, 2013). Conversely, network relationships are likely to drive mobility decisions, because a worker embedded in a social network is more likely to be informed of vacancies and to know more about the job and the receiving organisation. Third, spatial autocorrelation in mobility flows is taken into account using spatial econometrics techniques. Accounting for the dependence structure in mobility flows is an important issue (Bertoli and Moraga, 2013) and spatial filtering provides a natural tool to deal with such interdependencies (Patuelli et al., 2015).

Despite the commonly held belief that skilled workers are highly mobile in space, the analysis suggests that mobility remains a rare event. Among multi-patenting inventors, only 9.67% moved from one city to another between 1975 and 2008. Mobility is also limited in space; inventors who move travel between relatively large and co-located urban areas, and 90% of these moves occur within the same country. These results can be partly explained by the high level of circular and intra-firm mobility. Finally, the analysis highlight significant heterogeneity among countries, with about 80% of all moves taking place either in Germany, France or the UK. Likewise, the propensity to move vary importantly across technological sectors. Turning to the determinants of inventors' mobility, four results are worth noting. First, inventors are drawn toward cities offering numerous employment opportunities along with attractive working conditions. This finding is in line with the scarce existing evidence, provided by Miguelez and Moreno (2014) at the level of European regions, yet the explicit modelling of spatial autocorrelation and the analysis at the urban scale provide additional robustness to this finding. Second, the decision to move is mediated by network ties, which reduce information asymmetries between inventors and their potential employers, and therefore improve matching (Jackson, 2011). Besides, the definition of networks should not be restricted to direct collaborations. In particular, the centrality of cities, which represent a less restricted view of social networks, also plays a role. Third, contrary to expectations, geographical distance has a limited role in deterring mobility. This may be due to the availability of fast transportation across cities and because it acts as a proxy for other, more meaningful forms of distance. In particular, mobility occurs primarily between cities sharing the same technological specialisation, partly because of the availability of specialised jobs, partly because collaboration networks tend to develop within the same epistemic community. More importantly, cultural and institutional distance translate into greater adaptation costs. Fourth, from a methodological perspective, spatial autocorrelation in mobility flows is a serious issue and should be explicitly controlled for when estimating the gravity model in order to obtain unbiased parameter estimates.

These results have implications for the geography of innovation. While both mobility and networks have been shown to influence the diffusion of knowledge, they have often been investigated separately, and it would be interesting to study the interrelation between these two channels, as they appear to be closely related. Another implication concerns the ongoing construction of the European Research Area, a coordinated research system, which aims to facilitate the diffusion of local and external knowledge, in particular through the mobility of skilled individuals. The results suggest that the diffusion of knowledge may be limited for several reasons. Movers, represent only a fraction of the inventors; and those who move travel relatively short distances, generally within the same country. This result is magnified by the fact that a large portion of mobility occur within firms, and cannot be associated with a transfer of knowledge. Besides, the fact that mobility occurs primarily between technologically related cities may cause the transferred knowledge to be redundant, and have a limited economic impact. Finally, the results highlight significant heterogeneity across cities, and countries. A more promising finding is that mobility may be encouraged, in particular through the development of research collaborations involving distant research communities.

The remainder of this paper is structured as follows. Section 2 briefly reviews the related literature. Section 3 describes the data, with a focus on the definition of urban areas and the measurement of mobility. Section 4 provides descriptive figures to document the patterns of inventors' mobility across European urban areas, and their spatial dimension. Turning to the determinants of inventors' mobility, section 5 describes the model and discuss the estimation results. Section 6 concludes.

2 Background

Economists traditionally consider that mobility is a rational process in which workers compare expected utility at origin and destination to decide whether they should move. If workers expect to be better off living in another city despite the cost of moving, they will decide to move. Utility for a given city may depend on employment opportunities and the provision of amenities, and the cost of moving is expected to rise with distance, which acts as a proxy for pecuniary and non-pecuniary costs of moving. In this sense, mobility can be seen as a response to the spatial disparity in the provision of employment opportunities and amenities. Looking at employment opportunities in particular, workers would depart from cities where employment and wages are low toward cities where labour market conditions are the most attractive. This is particularly important for skilled workers as they tend to be more mobile and are more likely to benefit from better career opportunities. The concentration of skilled workers within the city may create a market pooling effect so that innovative firms may be drawn toward this location, thereby expanding employment opportunities and attracting additional skilled workers in a circular-causation mechanism. In the same spirit, skilled cities are more likely to host more entrepreneurs, which may employ the skilled population (Berry and Glaeser, 2005). However, purely economic factors cannot explain entirely mobility decisions, especially for the highly skilled. An alternative approach views mobility as a response to disparities in location-specific amenities such as climate and temperature (Graves, 1980). Building on this intuition, other economists have considered other human-produced amenities including public services and social, cultural and skill-dependent amenities which appear to be particularly important in an urban context (Florida, 2002; Shapiro, 2006). These two views are not incompatible in the sense that potential movers compare utility differentials across different alternative locations, and these utilities are a function of both economic and non-economic factors.

The above reasoning overlooks the fact that information about destination may not be easily available. Knowing about labour market conditions, or looking for a job in potential destinations may involve significant search and information costs. Social networks, spanned by friends and colleagues are important informal channels through which information are transmitted. The theoretical literature on social networks surveyed in Jackson (2011) has identified two main channels through which networks relationships can affect labour market outcomes. If a worker is embedded in a dense network, he is more likely to be informed of vacancies and to know more about the job and the receiving organisation. Such networks are particularly important for cross-country mobility, since workers may lack country specific skills such as language or knowledge of institutions. From the firms' perspective, professional networks may be used to improve screening and signalling of unobserved workers' ability, allowing them to select the most able workers. In sum, recruiting through professional networks may reduce information asymmetries and improve matching. Nakajima et al. (2010) provide empirical evidence on the importance of networks for matching inventors to firms. Using US patent data from 1975 to 1997, they show that networked inventors are more productive and have longer tenure than non-networked inventors. While we cannot observe in this paper whether inventors do use their networks when looking for a job, we can expect higher levels of mobility between cities whose inventors have collaborated frequently in the past. Krabel and Flother (2014) study the mobility of skilled German graduates entering the labour market.

They find that professional network ties directly impact job search success and labour mobility. Interestingly, they find that graduates are less likely to move when living in a metropolitan area where the share of highly qualified employees is relatively high.

Miguelez and Moreno (2014) study the mobility of inventors across European regions. Using EPO data from 1975 to 2005, they find that job opportunities and to a lesser extent, amenities are important determinants of inventors' mobility. Besides, they show that physical distance is a significant predictor of inventors' mobility patterns. Finally, other meaningful forms of distances such as social ties, institutional framework and cultural similarities are shown to play a role. Looking at geographical distance in particular, Breschi and Lenzi (2010) document the mobility patterns of US inventors. Using EPO data from 1978 to 2004, they investigate mobility in space and across firms at both the metropolitan and micropolitan level. Their result highlight the existence of two distinctive spatial patterns, whereby inventors move both at short and long distances. Some evidence is also available for other categories of skilled workers. In an urban context, Scott (2010) investigate what drives inflows of migrant US engineers into different MSAs for 13 different technological categories, he finds that local employment opportunities have a major impact on the destination choices of these skilled individuals, far above amenities or even wages. Dorfman et al. (2011) find that natural amenities are not a major factor of high-tech workers' location decisions and metropolitan areas of the United States. Nifo and Vecchione (2014) study the importance of institutions on the mobility decisions. Using a sample of 47300 Italian graduates, they find that institutional quality is a major determinant of inventors' mobility. Faggian and McCann (2006, 2009) study the migration of UK graduates entering into first employment. The analysis suggests that more educated individuals are more likely to move. Besides, migration flows are mainly directed by differences in nominal wages so that, regions offering a higher nominal wage are net absorber of human capital flows and regions with lower nominal wages net losers of human capital. More interestingly, a centre-periphery pattern seems to emerge which reflects the rank order of the region within the national urban hierarchy.

Additional evidence on the determinants of inventors' mobility adopt a more microeconomic approach. Crespi et al. (2007) investigate the factors that drive the mobility of inventors from academia to the private sector using a sample of academic inventors who were granted a EPO patent between 1993 and 1997. They report that individual life cycle is important for all kinds of mobility. Besides, mobility patterns are found to differ greatly across technological sectors and countries. Which suggest the importance of academic labour market regulations and institutions. Hoisl (2007) studies the interrelation between inventors' productivity and inventors' mobility using a random sample of 2697 inventors who were granted EP patents between 1993 and 1997 while residing in Germany. Findings indicate a simultaneous relationship. Movers are on average more productive than non-moving inventors, but more productive inventors are also less likely to move. In a similar setting, Lenzi (2009) studies the microeconomic determinants of the mobility patterns of 106 Italian inventors in the pharmaceutical sector. The analysis points out that inventor's personal characteristics, inventive productivity, and geographical location matter for mobility choices. The results also show a positive association between productivity and mobility.

The descriptive part of this study is closest to Breschi and Lenzi (2010) who document the mobility patterns of inventors across US Core Based Statistical Areas (CBSA) between 1978 to 2004. To my knowledge, no comparable evidence is available for Europe, especially at the level of cities. This would be interesting because mobility patterns in Europe are expected to be quite different from the United States for several reasons. First, it is well-known the Europe exhibit lower levels of mobility than the United States, both regarding the degree and the spatial extent of mobility. However, differences do not only include mobility patterns. Most empirical evidence from Europe suggests that mobility is driven mainly by labour market variables rather than amenities (Miguelez and Moreno, 2014). Finally, there is very little evidence on the importance of network ties in driving the mobility decisions of European inventors, though some evidence is available for the United States (Nakajima et al., 2010).

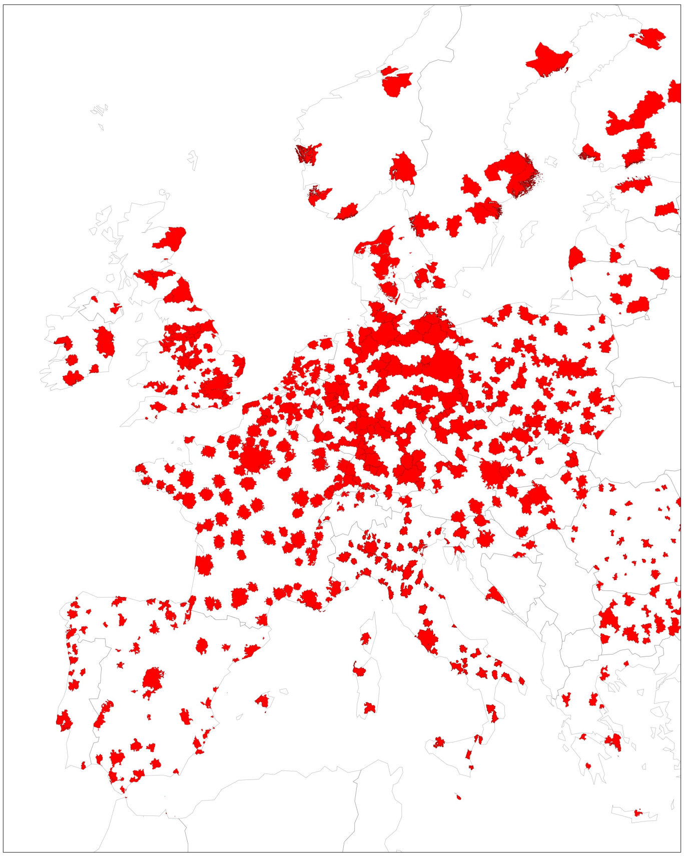
3 Data and variables

Measuring urban areas

Larger Urban Zones (LUZ) were created by the Urban Audit project to provide a harmonized definition of metropolitan areas throughout the EU as well as several other countries. In the 2012 version, which uses 2006 as a reference year, LUZ are defined on the basis of population size, population density and commuting patterns, so that each one represents a self-containing labour market (Djikstra and Poelman, 2012). This edition covers 695 cities in 31 countries[1].

[1] The 28 European Union current member States, Norway, Switzerland and Iceland.

Figure 1: Larger Urban Zones as of 2006



Specifically, each LUZ is composed of a densely populated city core and a commuting zone around it. The urban core is composed of high-density contiguous population grid cells (> 1500 inh/km^2) whose total population is greater than 50000. The core is then adjusted to LAU2 delineations[2] and include those LAU2 with at least 50% of their population inside the urban core. The commuting zone includes LAU2 where more than 15% of their employed resident population work within the urban core. To ensure homogeneity, LAU2 surrounded by a single LUZ are included and non-contiguous LAU2 are dropped.

Measuring mobility

Mobility is computed from the Invpat database (Lai et al., 2013). The database contains all inventor-patent instances at the USPTO from 1975 to 2010 and includes information about inventors, patents and assignees[3]. Mobility is computed by recording changes in inventors' personal addresses. Consider an inventor who fills a patent at time t while residing in city i; in $t + 2$, this

[2]LAU2 consists of municipalities or equivalent units in the 28 EU Member States.

[3]The database contains inventors' names and addresses, assignees' names, patent numbers, dates of application and granting and detailed technological classes.

same individual fills another patent while residing in city j. Therefore, we can say that between t and $t + 2$, this individual has moved from i to city j. This measure of mobility is fairly straightforward but presents three obvious drawbacks. First, the use of patent data restricts the analysis to those inventors with at least two patents, when single-patenting inventors represent about 56% of the sample. Second, a move is recorded only if those inventors applied for a patent before and after the move, so it represents a lower-bound measure of mobility. Third, patents record inventors' location at a point in time, therefore it is not possible to determine precisely when the move took place. I consider that mobility occurs exactly between the application dates of the patents at origin and destination, if there is no more than a four-year lag between the two. Addresses are then geolocated at the level of LUZ. Mobility computed this way identifies inventors who filled at least two patents while residing in different LUZ.

Another issue is that in practice, it is difficult to determine whether two inventors are the same person, since the USPTO does not require unique identifiers for inventors. Therefore, disambiguation is necessary to determine whether two patents belong to the same inventor career by comparing all pairs of inventor-patent instances. In particular, two issues arise from this exercise. The first is misspelling of the same inventor name on different occasions while the second occur when two inventors with exactly the same name are not actually the same person. To overcome this difficulty, Lai et al. (2013) disambiguation algorithm uses most information in patent documentation to identify likely matches[4]. The routine computes a cumulative similarity score for each pair of inventor-patent instances, the greater the similarity score, the greater the probability that the two patents belong to the same inventor career. The threshold value of the score has been set to a relatively high value to ensure a rather conservative approach.

[4] Variables used for the disambiguation include first names, middle initial, last names, location, assignees, number of shared technology classes, and number of shared co-inventors.

Explanatory variables

Table 1: List of variables

Variables	Proxies	Sources
Mobility of inventors	Changes in patenting addresses	Invpat
Economic size	Population, Number of inventors	Invpat, UG
Distance	Geographical distance, Driving distance	UA
Employment opportunities	Human resources in S&T, R&D spending	Eurostat
Networks of inventors	Collaboration counts, Betweenness centrality index	Invpat
Technological proximity	Technological proximity index	Invpat
Culture, Institutions	Same country dummy	UA

Note: UA stands for the Urban Audit and UG for the University of Geneva.

Gravity variables

The gravity variables include economic size and distance. In migrations studies, a common practice is to use population rather than economic variables such as GDP. In this paper, the number of inventors at origin and destination is used to measure the number of potential movers. Intuitively, a higher level of mobility is expected between cities with a large stock of inventors. Distance is measured in several ways including geodesic and driving distance (Luxen and Vetter, 2011) between LUZ geographical centres. Distance between origin and destination is expected to reduce inventor flows for at least three reasons. First, the direct cost of moving is higher, these cost may include transportation and other pecuniary costs involved in the relocation. Second, distance increases search costs and reduces the quality of information about the destination, such as job opportunities or income differentials. Finally, movers may also face significant non-pecuniary costs. If he has spent a substantial amount of time in the city of origin, moving to a distant city means being separated from family and colleagues (Dahl and Sorenson, 2010).

Variables of interest

Employment opportunities are measured using the total human resources in science and technology. This variable measures the number of workers that either successfully completed tertiary-level education or are employed in a science and technology occupation. It is a general proxy for human capital, the presence of universities, research centres and technology-oriented firms. In addition, total R&D spending captures the investment in knowledge creation from the public and the private sector, and is a proxy for the research effort. The expected impact of these variables is unclear at least for the city of origin. On the one hand, cities with a large labour market for inventors host more potential movers, which increases the probability of a move. On the other hand, working in a city where many firms, universities, research centres are located makes it easier to move within the area, and to the extent that intra-city mobility is a substitute to inter-city mobility, this decreases the probability of a move.

A network of inventors can be viewed as a social network whose nodes are individual inventors and links are co-inventorship relations. Co-inventorship refers to the situation where the patent lists more than one individual as inventor. If two inventors have collaborated in the past, a social tie exist. The network variable full counts for each year the number of collaborations between inventors residing in city i and those residing in j. I acknowledge a certain degree of endogeneity between the network variable and the dependent variable since mobility influences the structure of networks by creating new, bridging or closing existing networks. To attenuate this issue, the network variable is lagged one year.

In addition, a measure of centrality is used to abstract from the duality of the network variable, which represents a rather restrictive view of social networks. In this paper, centrality measures the relative position of a city within the network. It characterizes whether a particular city has a favourable position in the network and how a city's network positioning changes over time. Following Berge et al. (2015) the Betweenness Centrality index (BCi) of a city breaks down into three main components. (1) A city's participation intensity, which measures of how well a city is embedded in the network of collaboration. (2) A city's relative outward orientation, which assesses the openness of a city with respect to established network linkages. A high number of internal collaborations would have a negative influence as it potentially reduces the number of actors connecting different cities. (3) A city's diversification of network links, which indicates how collaborations are distributed along other cities in the network. The more concentrated the collaborations, the less the region is central in the sense that it links only a few other cities. The BC of a city, which is defined as the number of bridging paths stemming from a city between all dyads of the network, can be defined as

$$BC_i = \sum_{i \neq j} \sum_{k \neq i,j} \frac{g_{ij} g_{ik}}{n_i} \tag{1}$$

n_i is the number of inventors active in region i. g_{ij} and g_{ik} are the network links between city i

and city j or k, respectively. In an aggregate context, equation (1) collapses to[5]

$$BCi = \bar{g}_i s_i (1 - h_i) \tag{2}$$

$\bar{g}_i = g_i - g_{ii}$ is the number of outer collaborations, and reflects the participation intensity of the city. $si = \bar{g}_i/g_i$ is the share of outer collaborations, which measures the relative outward orientation of the city. $hi = \sum_{k \neq i,j} (g_{ij}/\bar{g}_i)^2$ is the Herfindahl-Hischman index of the distribution of i's outer collaborations. It varies between zero and one depending on the degree of diversification of network links to other cities. The resulting centrality index is normalized to one, so that the most central city has an index value equal to unity. As for the previous network measure, inventors flows are expected to be positively associated to the BC index.

Control variables

Technological proximity. Inventors may be specialized in a very specific field, and do not have many alternative destination to choose from. In an aggregate context, a technological distance index is computed by grouping the patents into technological sectors and comparing their relative distribution across cities. Using the classification provided by the NBER patent data project, patents are grouped into 6 broad technology classes and 40 subclasses. Patents associated with more than one technological class count once in each category. Following Jaffe (1986), technological proximity is computed as the uncentered correlation between i and j's vectors of technological class, so that

$$t_{ij} = \frac{\sum f_{ih} f_{jh}}{\sqrt{\sum f_{ih}^2 \sum f_{jh}^2}} \tag{3}$$

f_{ih} and f_{jh} denote the share of city i and j's patents of technological class h, respectively. The resulting index t_{ij} varies between zero and one depending on the level of technological proximity. The technological proximity index is computed using 34 technological subclasses[6]. An index value close to unity indicates that two cities are technologically similar, while a value close to zero indicate that they are technologically distant. Inventors flows are expected to be larger between cities that have a similar technological specialisation.

Institutional and cultural proximity. Even though workers are in principle free to move, they are

[5]See Berge et al. (2015, p. 20-21) for formal proof.

[6]Each of the 6 class has a subclass named "Miscellaneous", which is considered too heterogeneous to reflect a city's technological specialisation.

in practice confronted with a series of obstacles hampering their movement. Differences in culture, language, institutions may translate into greater adaptation costs. Inventors' mobility may be hampered by institutional and legal barriers, which may vary significantly across countries. In the same manner, inventors are more likely to relocate in a city sharing the same cultural background and language, in order to minimize mobility costs. Institutional and cultural proximity are captured using a dummy variable that takes the value one if the two cities are located in the same country and zero otherwise. Intuitively, inventors flows are expected to be smaller between cities belonging to different countries.

Table 3: Descriptive statistics

	Mean	St. Dev.	Min.	Max.
Stock of inventors	53.8	159.6	0	2676
Number of patents	50.8	141.4	0	2195
Geographical distance	807.2	452.9	10	3120
Driving distance	974.0	549.2	13	3830
Human resources in S&T	4999.4	55302.7	0	1535794
R&D expenditures	332.8	3921.5	0	110877
Collaborations count	0.1	2.8	0	522
Betweenness centrality index	0.0	0.1	0	1
Technological proximity	0.2	0.2	0	1

4 Patterns of inventors' mobility

This section documents the patterns of inventors' mobility across LUZ between 1975 and 2008. During this period, 72.62% of all patents were filled by inventors residing in urban areas. This share, although substantial, is somewhat lower than that reported by Jaffe et al. (1993) for the United States. Among multi-patenting inventors, only 9.67% were mobile, which suggest that mobility is a rare event, and contradicts the commonly held belief that skilled workers are highly mobile in space. The final sample includes 15361 inventors who moved across at least two of the 695 LUZ between 1975 and 2008, for a total of 30628 moves. Table 4 shows that about 80% of inventors moved only once or twice during their career. Likewise, the number of cities visited, defined as the number of different cities where an address has been recorded, exhibit a large positive skew, which suggest that circular mobility is important.

Table 4: Distribution of inventors per number of moves and cities visited

Nb. moves	Nb. inventors (%)	Nb. cities	Nb. inventors (%)
1	9045 (58.88)		
2	3361 (21.88)	2	13881 (90.37)
3	1230 (8.01)	3	1246 (8.11)
4	666 (4.34)	4	173 (1.13)
5+	1059 (6.89)	5+	61 (0.40)
Σ	15361 (100)	Σ	15361 (100)

Circular mobility is identified when the city of origin for the move m is the same as the city of destination for the move $m+1$. Each pair of moves is compared in sequence for the 6316 inventors who moved at least twice during their career, for a total of 15267 moves. This is a rather restrictive approach of circular mobility since each move is compared only with the next, so this is probably a lower-bound measure. Nonetheless, this form of mobility represents about three-quarters (74.08%) of these inventors' mobility.

Building on these considerations, one may wonder whether circular mobility occurs because inventors move primarily between different establishments of the same firm (Breschi and Lenzi, 2010). For instance, if the inventors works for a multinational firm, changing location does not imply working for another firm, but simply moving from one facility to another. In this sense, intra-firm mobility is defined as a move between two establishment of the same firm located in two distinct cities. Establishing whether two assignee are in fact the same firm is difficult, since the assignees' names alone cannot be used to identify the firm that holds the patent. Problems arise from misspellings, from different forms of the same company's name and from subsidiaries having completely different names from the parent. Lai et al. (2013) performed a disambiguation of firms names using the NBER file of patent assignee to identify the same firms listed as assignee on distinct patents. The following figures should be interpreted with caution as information about the assignee at both origin and destination is available in only 66.85% of the cases. In this sub-sample, intra-firm mobility represents 69.64% (14259) of the moves so that inter-firm mobility is limited. Linking this to circular mobility, among inventors the 4449 inventors who moved at least twice, and for which assignee information is available, about half (49.23%) of circular mobility occurs within the same firm, suggesting that the two phenomena are closely related. Speculatively, this could point to the importance of collaboration networks in the mobility decisions of inventors. A more formal analysis is carried out in the next section.

Table 5: Distribution of moves per country

Country	National moves	International moves	
		as origin (%)	as destination (%)
Germany	14227 (51.74)	813 (25.96)	745 (23.79)
United Kingdom	5997 (21.81)	448 (14.30)	399 (12.74)
France	2693 (9.79)	349 (11.14)	384 (12.26)
Netherlands	1201 (4.37)	300 (9.58)	286 (9.13)
Italy	1081 (3.93)	122 (3.90)	144 (4.60)
⋮			
Belgium	288 (1.05)	217 (6.93)	242 (7.73)
Switzerland	172 (0.63)	304 (9.71)	319 (10.19)
Austria	82 (0.30)	177 (5.65)	195 (6.23)
Others	1755 (6.37)	402 (12.82)	451 (14.4)
Σ	27496 (100)	3132 (100)	

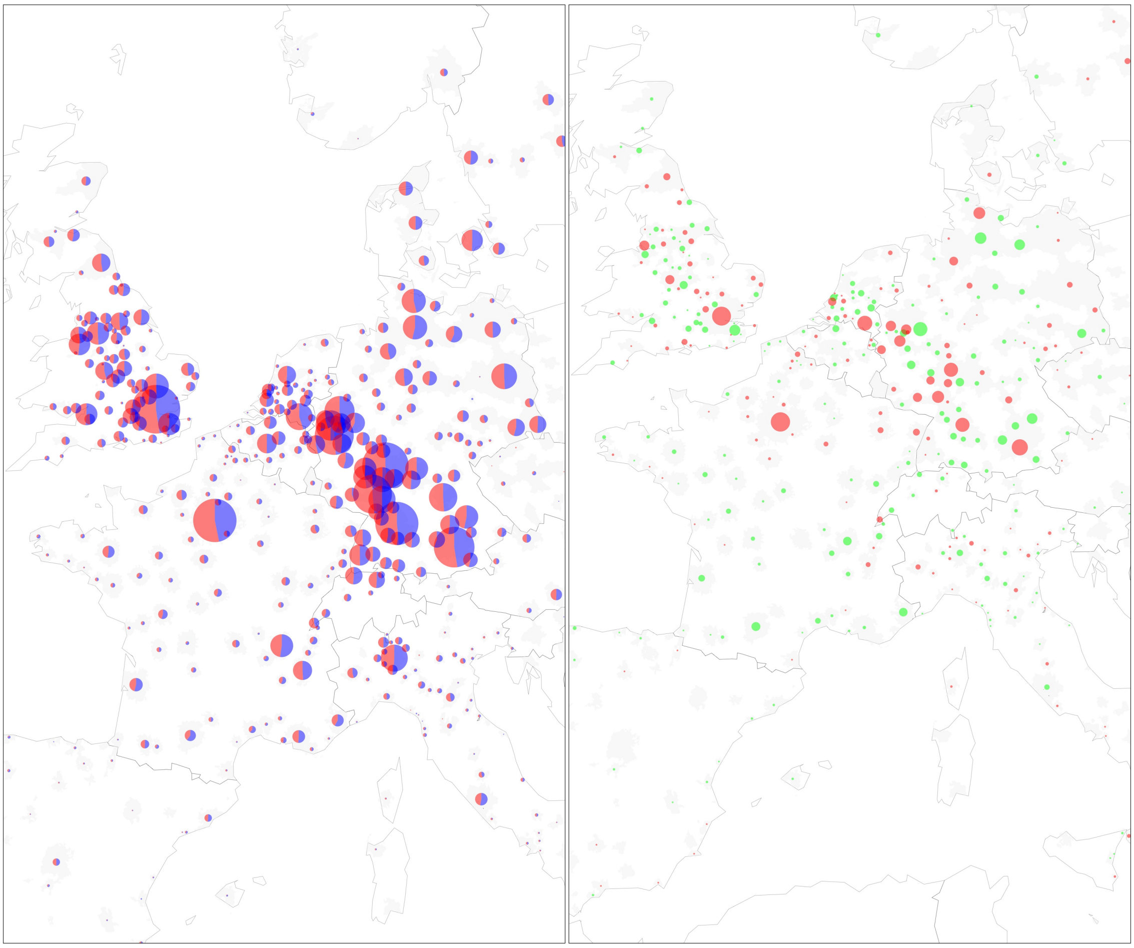
Note: The upper panel lists the top 5 countries according to the total number of moves. Belgium, Switzerland and Austria are listed due to their high level of international mobility. There are 28 countries in total.

Turning to the spatial dimension of mobility, table 5 describes the distribution of national and international moves per country. Here, three figures are worth noting. First, Germany represents about half of all national moves and a quarter of international moves. This can be explained by the importance on intra-firm and circular mobility and by the higher level of patenting activity in Germany, which represents 39.69% of all patents. Second, 89.77% of the mobility occur within the same country, whereas international mobility only represents a fraction of the moves. Interestingly, in Belgium, Switzerland and Austria, the magnitude of international mobility both as origin and destination is much higher than in the other countries. Speculatively, this countries may act as international hubs in the mobility of inventors, partly due to their central location in Europe and their reliance on foreign workers due to the small size of their domestic labour market. Finally, both national and international mobility take place across relatively short distances, while inventors who move nationally travel on average 180 km, the mean driving distance for those who move across borders is 532 km. Both these figures are much lower than those reported by Breschi and Lenzi (2010) who show that mobile US inventors travel on average 867km[7]. The distribution of moves by distance has a large positive skew, which means that the vast majority of moves take place across

[7] Moves to Alaska, Hawaii and Puerto Rico are excluded.

short distances. This goes against the argument that high-skilled individuals are less affected by physical distance in their location decisions, as they are positively selected and in consequence they are more likely to move and to move further away.

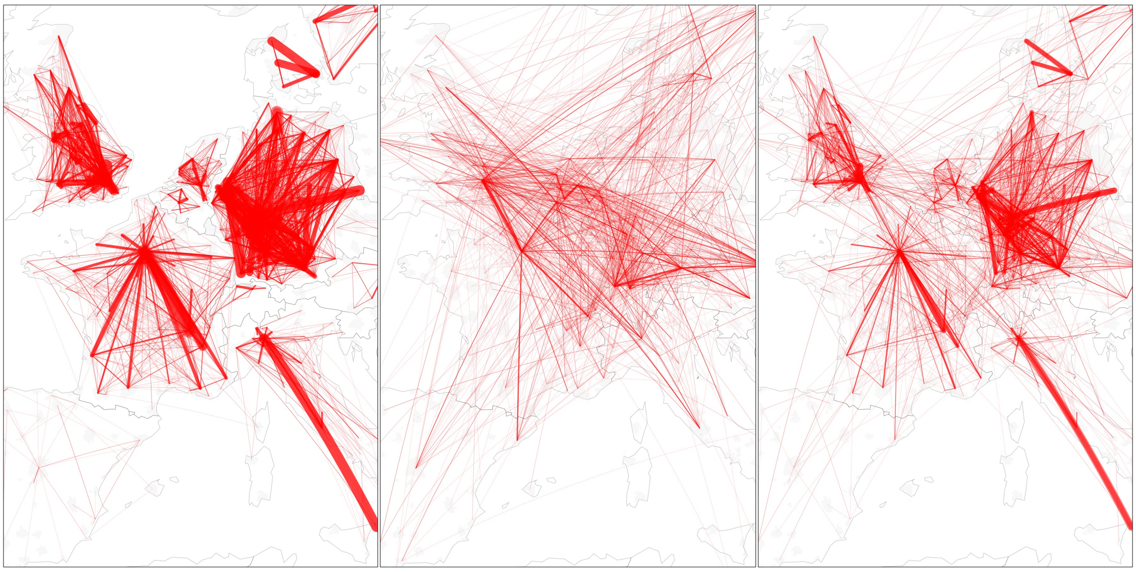
Figure 2: Inward, outward (left) and net (right) mobility of inventors at the LUZ level



Left: Inward mobility is in blue while outward mobility is in red. The size of the largest bubble corresponds to 2495 moves (inward + outward). Right: Positive net mobility is in green while negative net mobility is in red. The size of the largest bubble corresponds to a 126 moves difference between inward and outward mobility.

Looking at a finer spatial scale, figure 2 depicts the distribution of inventors' mobility across LUZ. The left panel confirms earlier findings that mobility occurs primarily between a selected number of large urban areas, such as those located in the Rhur, southern UK, or Paris and Milan. Interestingly, the distribution of inward and outward mobility is remarkably similar, as confirmed by the right panel. This result may be explained by the large amount of short-range circular mobility. This suggest that we should not think of mobility between cities in terms of attraction and repulsion, at least in our case, more dynamic areas are associated with a larger turnover, with large inward and outward mobility, than less dynamic areas. In a more dynamic setting, figure 3 depicts national, international and circular movement of inventors. The dynamics of internal mobility vary greatly across countries and reflect the diverse urban configurations in these countries (see figure 1). Paris and London occupy central position in the mobility network of their respective countries, while in Germany, moves appear more evenly distributed across the urban continuum. Interestingly in Italy, there is a high level of circular mobility between Milan and Messina.

Figure 3: National (left), international (middle) and circular (right) mobility of inventors



Finally, mobility patterns vary according to the technological specialisation of inventors. Each patent has a list of technology classes, which provides information about the inventors's area of expertise. However, assigning a particular technological sector to inventors is difficult for at least two reasons. First, some inventors work in multiple fields, or are specialised in activities belonging to two related but distinct technological fields. In this case, the inventor's patents would list multiple technological classes, some of which belong to different sectors. Second, a patent often has more than one designated inventor, and the relative contribution of each inventor to the patent is unknown. This may be problematic when a patent is filled by an interdisciplinary team where inventors are specialised in distinct sectors. For each inventor, classes of the patents he has filled during his career are grouped one of the six technological sectors defined previously. A patent listing more than one class give rises to as many class occurrences. The first specialisation is defined as the sector which appear most often in an inventor career and represent at least 40% of the listed patent classes. Following the same selection rule, a second specialisation may be defined for those inventors who engage in cross-sector activities. Using this criterion, less than a third (27.81%) of mobile inventors are specialised in two sectors, the majority of them being specialized first in the chemical sector, and having the drugs & medical sector as a second specialisation. Table

7 shows the number of inventors and the distribution of moves per technological sector using the first specialisation of inventors.

Table 7: Distribution of moves per technological specialisation of inventors

Technological sector	Nb. inv.	National	International	All
Chemical	5583	11615	1174	12789
Computers & communications	1852	2864	394	3258
Drugs & medical	1326	2220	409	2629
Electrical & electronic	2486	3984	512	4496
Mechanical	2472	2280	250	4454
Others	1411	2118	241	2530
Σ	15130*		30156*	

*472 moves were made by the 231 inventors with no specialisation according to this definition.

Note that the propensity to patent may be greater in some sectors. The greater the number of patents, the greater the probability to observe a move across LUZ. Therefore, observed mobility in those sectors may be inflated in comparison to others sectors with a lower propensity to patent.

5 Determinants of inventors' mobility

5.1 The model

The model is based on the well-known utility maximizing framework. Assuming that inventors are rational and freely mobile, their decision to move from one city to another is based on a comparison between the expected utilities at origin and destination. In this setting, the individual utility is a function of location-specific variables, and the cost of moving is a function of distance between origin and destination. Formally, the utility of individual k associated with city i can be written

$$U_i^k = u(X_i) + \epsilon_i^k \tag{4}$$

The model states that the individual utility from living in i, depends on a component common to all individuals $u(X_i)$, and a stochastic term ϵ_i^k, which represent factors specific to inventor k. These factors include anything that leads k to value X_i differently than a randomly selected individual. By definition, $E(\epsilon_i) = 0$, since any systematic component is included in u. It follows that an individual decides to move if the expected utility differential is greater than the cost of moving.

$$E(U_i^k) < E(U_j^k) - C(d_{ij}) \tag{5}$$

When this condition is satisfied, the mobility variable takes the value one and zero otherwise. By aggregating individual movements by cities using a gravity model specification, we can write

$$Y_{ij} = \beta_0 X_i^{\beta_1} X_j^{\beta_2} X_{ij}^{\beta_3} \epsilon_{ij} \tag{6}$$

Y_{ij} is a $n^2 \times 1$ vector of flows between i and j. X_i and X_j are $n^2 \times p$ matrices representing the p characteristics at origin and destination, respectively. Similarly, X_{ij} is a matrix representing the origin-destination characteristics. β_0 is a vector of ones and β_1, β_2, β_3 are scalar parameters to be estimated. Finally, ϵ_{ij} is a vector of disturbances with $E[\epsilon_{ij}|X_i, X_j, X_{ij}] = 1$ assumed to be statistically independent from the explanatory variables. This leads to

$$E[Y_{ij}|X_i X_i X_{ij}] = \beta_0 X_i^{\beta_1} X_j^{\beta_2} X_{ij}^{\beta_3} \tag{7}$$

The dependent variable takes non-negative integer values, many of which are zero, which invalidates the normality assumption, especially when the range of values taken by the dependent variable is limited. Santos Silva and Tenreyro (2006) propose to overcome this issue using a Poisson specification of the gravity model along with the Poisson Pseudo Maximum Likelihood (PPML) estimator proposed by Gourieroux et al. (1984). The PPML estimator is like the Poisson maximum likelihood estimator except that the data generating process used does not need to be the Poisson. This estimator has been shown to be robust to different patterns of heteroskedasticity and conveniently deals with the zero values, as the model can be estimated in its multiplicative form. The PPML estimator has the appealing feature coefficients estimates can be interpreted in terms of elasticities if the dependent variable is in level and the covariates are in logarithms. A profitable approach is to model the expected value as an exponential function. Because the exponential is always positive, it ensures that predicted values for Y will also be positive. Assuming that observed mobility flows follow a Poisson distribution with μ_{ij} as the expected flows, and are independent of other mobility flows, the observed flows have the probability distribution

$$Prob(y_{ij}) = \frac{exp(-\mu_{ij})\mu_{ij}^{y_{ij}}}{y_{ij}!} \tag{8}$$

The parameters and expected flows of a Poisson regression model can be estimated with maximum likelihood techniques. Following Krisztin and Fischer (2015), equation (7) can be rewritten as

$$\mu_{ij} = E[Y_{ij}|X_i X_i X_{ij}] = \exp[\ln \beta_0 + \beta_1 \ln X_i + \beta_2 \ln X_j + \beta_3 \ln X_{ij}] \tag{9}$$

Maximum likelihood estimation of the Poisson regression model assumes that all observations are mutually independent. In a gravity setting, this implies that mobility flows between any pair of cities is independent from flows between any other pair of cities. Such an assumption is not likely to hold for several reasons. First, movers face a discreet choice in choosing between alternative destinations (Beenstock and Felsenstein, 2013). If a mover living in city i can choose either cities j or k as alternative destinations, it follows that flows from i to j are not independent from flows from i to k. Second, mobility flows between a pair of cities does not only depend on their respective attractiveness, rather, it is influenced by pull and push factors across all possible origins and destinations, the multilateral resistance to migration (Bertoli and Moraga, 2013; Behrens et al., 2012). As a result, model residuals may exhibit spatial autocorrelation, which directly violates the independence assumption, and produce consistent but biased parameter estimates (Krisztin and Fischer, 2015). The problem of alternative destinations is analogous to one that arises in the gravity model of international trade. In their influential contribution, Anderson and van Wincoop (2003) argued that accounting for the interaction structure is important when estimating the gravity equation. A variety of approaches have been taken to control for multilateral resistance, from the inclusion of ad-hoc remoteness index to the introduction of origin and destination-specific indicator variables. This latter solution is not satisfactory for at least two reasons. First, Behrens et al. (2012) and Koch and LeSage (2015) argue that the inclusion of origin and destination fixed effects captures heterogeneity rather than spatial dependence. Second, city-specific determinants of mobility cannot be estimated. Recently, Patuelli et al. (2015) show that the inclusion of origin-specific and destination-specific spatial filters effectively control for omitted multilateral resistance terms while filtering out autocorrelation in mobility flows. The rationale is that many mobility cost variables such as distance, culture or institution are spatially correlated, so that spatially proximate cities tend to have similar resistance terms.

In this framework, we distinguish two forms of spatial dependence in a gravity framework[8]. Origin-based dependence assumes that flows from an origin to a destination are correlated with other flows from neighbours to origin to the same destination. Conversely, destination-based dependence assumes that flows from an origin to a destination are correlated with other flows from the same origin to neighbours to destination. Connectivity is introduced in the model using a W matrix.

[8]The structure of dependence in a gravity framework is more complex in the sense that each city is associated with several observations as an origin and as a destination.

One issue is that W cannot be estimated and needs to be specified in advance, using some relevant criterion. The specification of W is always subject to arbitrariness and it has become common practice to investigate whether results are robust to the specification of W. However, LeSage and Pace (2014) argue that estimates should not be overly sensitive to changes in the weight matrix in a well-specified spatial model. The preferred specification of W is based on cut-off driving distance. Specifically, two cities are considered as neighbours when their respective geographical centres are located within 150km of each other[9]. Formally,

$$W_{ij} = \begin{cases} 1 & \text{if } d_{ij} \leq 100 \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

The resulting W matrix is a $n \times n$ sparse and symmetric matrix with zeros on the diagonal and and ones on the off-diagonals when observation i depends on observation j. The W matrix is then used for spatial autocorrelation diagnostics and to compute the spatial filters. Traditional diagnostics may not be appropriate for Poisson residuals (Chun, 2008). Instead, I follow Lin and Zhang (2007) and use a Moran's I log-linear residual test to detect spatial autocorrelation in the residuals.

Eigenvector spatial filtering was introduced by Griffith (2003) for areal data and recently extended to flow data. Applications to mobility flows[10] include United States interstate migration (Chun, 2008; Chun and Griffith, 2011), and German journey-to-work flows (Griffith, 2009). This approach is based on the assumption that spatial autocorrelation in the disturbances arises from missing origin and destination variables, which are spatially autocorrelated (Tiefelsdorf and Griffiths, 2007), very much like the missing origin and destination multilateral resistance terms. A spatial filter made of synthetic variables that serve as surrogate for spatially autocorrelated missing origin and destination variables can be used to control for spatial autocorrelation[11]. This approach has the advantage that the model can then be estimated as if observations were independent, using conventional regression techniques. This is particularly attractive in our case where the dependent variable represents Poisson distributed counts, because conventional spatial regression models are less developed for these types of data.

Specifically, spatial filtering relies on the spectral decomposition of a transformed W into eigenvalues and eigenvectors, and then uses a subset of eigenvectors as origin and destination explanatory

[9] A shortcoming to this approach is that interdependencies are not merely spatial (Behrens et al., 2012; Beenstock and Felsenstein, 2013)

[10] Other applications to flow data include trade (Krisztin and Fischer, 2015; Patuelli et al., 2015), patent citations (Fischer and Griffith, 2008) and research collaborations (Scherngell and Lata, 2013).

[11] In the presence of spatial autocorrelation, the residuals can be divided into a spatial component and the white noise. Spatial filtering enforces independence by isolating the stochastic spatial component from the white noise using a set of proxy variables called a spatial filter. The model can then be estimated using standard regression techniques that assume independence among the observations.

variables in the model. Eigenvectors can be interpreted as independent map patterns describing the latent spatial autocorrelation of a variable. The W matrix is transformed as follows

$$\left(I - \frac{ll'}{n}\right) W \left(I - \frac{ll'}{n}\right) \tag{11}$$

I is the $n \times n$ identity matrix, l is an $n \times 1$ vector of ones and l' its transpose. The n eigenvector of the above matrix describe the full range of possible and mutually orthogonal uncorrelated map patterns, and their corresponding eigenvalues index the nature and degree of spatial autocorrelation portrayed by each eigenvector. Eigenvectors are extracted in sequence to maximise the Moran Coefficient (MC) while being uncorrelated with the preceding eigenvectors. For parsimony, it is not sensible to include all eigenvectors in the spatial filter, a two-step procedure is used to identify a relevant subset of eigenvectors. First, eigenvectors are selected on the basis of their MC values exceeding some predefined threshold. Here, the common rule $^{e_i}/_{e_1} \geq 0.25$ is used, where e denotes the associated eigenvalues, to keep eigenvectors associated with strong and positive spatial autocorrelation. This subset is further reduced through a stepwise Poisson selection technique[12] (Tiefelsdorf and Griffiths, 2007). Filters at origin and destination are obtained using $E_i = l \otimes E$ and $E_j = E \otimes l$ respectively, where E is the $n \times Q$ matrix of eigenvectors and the resulting E_i and E_j are $n^2 \times Q$ matrices, Q being the number of selected eigenvectors. The spatial filter includes the subset of Q eigenvectors that are common to all cross-sections. Following Krisztin and Fischer (2015), adding the spatial filter to equation (7) gives:

$$\mu_{ij} = exp\left[\ln \beta_0 + \beta_1 \ln X_i + \beta_2 \ln X_j + \beta_3 \ln X_{ij} + \sum_{q=1}^{Q} E_q \Phi_q\right] \tag{12}$$

Where $exp\left[\sum_{q=1}^{Q} E_q \Phi_q\right]$ is the spatial filter that accounts for origin and destination spatial autocorrelation. E_q denotes the q^{th} eigenvector and Φ_q its associated coefficient.

5.2 Results

This section summarizes the main estimation results obtained. The sample used is restricted to inventors who moved across $n = 497$ LUZ between 2000 and 2007, for which explanatory variables are not missing. To avoid extreme heterogeneity, I follow Miguelez and Moreno (2014) and pool

[12]As noted by Patuelli et al. (2015), selection based on AIC or BIC is not possible in the case of Quasi-Poisson models since they have no likelihood, so it is manually performed by iterative backward elimination of the eigenvector with the highest p-value.

mobility flows into two distinct four-years periods[13], the first corresponding to 2000-2003 and the second to 2004-2007. Table 8 presents the estimation output for the unfiltered PPML gravity model in columns (1) and (2) and its spatially filtered counterpart in columns (3) and (4). Given that the large majority of moves occur between German cities, table 9 in the annex reports the regression output for a subset of observations excluding German cities, both as origin and destination. Results remain robust as both the significance and the relative ordering of coefficients remain unchanged.

Broadly speaking, all coefficients estimates in table 8 have the expected sign and significance. The adjusted Moran'I is positive and significant at the 1% level in the two periods. In a mobility context, this means that inventors' flows between two cities tend to be positively associated with flows in neighbouring cities, either at origin or destination. This result suggest that spatial autocorrelation in mobility flows should be explicitly controlled for when estimating the gravity model in order to obtain unbiased parameter estimates. The selected eigenvectors effectively fill this purpose, as shown by the adjusted Moran's I, which is divided by about 4.5 when adding the spatial filter. As a result, the spatially filtered model consistently exhibit lower standard errors than its unfiltered counterpart, and the goodness-of-fit measure indicates that this model is the preferred specification.

[13]In this study, I do not implement the panel specification. In fact, the main advantage of using the longitudinal structure of the data would be to include origin-destination-pairs fixed effects, to account for time-invariant pair-specific unobserved heterogeneity that is not captured by the covariates. Using random effects would be inappropriate here because we cannot assume that unobserved heterogeneity is related with unobserved effects that are time-invariant and not specific to origin-destination pairs (Scherngell and Lata, 2013). A disadvantage of fixed effects is that time-invariant variables cannot be included in the model. However, variables such as geographical distance, cultural and institutional proximity are of special interest for this study. With regards to spatial dependence, fixed effects do not effectively control for spatial autocorrelation and precludes the use of a spatial filter. A time-varying spatial filter would rely on a connectivity matrix specific to each period, and there is no theoretical motivation to do so in this study. Besides, the eigenvector selection procedure in a panel framework is unclear from a mathematical point of view (Patuelli et al., 2011).

Table 8: Cross-sectional estimation results

	Unfiltered Quasi-Poisson		Spatially filtered Quasi-Poisson	
	00-03 (1)	04-07 (2)	00-03 (3)	04-07 (4)
Stock of inventors (orig)	0.608***	0.495***	0.634***	0.536***
	(0.033)	(0.050)	(0.014)	(0.020)
Stock of inventors (dest)	0.510***	0.425***	0.556***	0.509***
	(0.038)	(0.065)	(0.017)	(0.025)
Driving distance	−0.379***	−0.324***	−0.312***	−0.226***
	(0.063)	(0.083)	(0.018)	(0.026)
R&D expenditures (dest)	0.522***	0.313***	0.649***	0.568***
	(0.064)	(0.092)	(0.031)	(0.046)
Human res. in S&T (dest)	0.614***	0.443***	0.699***	0.659***
	(0.059)	(0.067)	(0.027)	(0.041)
Collaborations count	0.686***	0.790***	0.649***	0.710***
	(0.035)	(0.043)	(0.010)	(0.015)
Betweenness centr. (orig)	0.259***	0.162*	0.278***	0.128***
	(0.052)	(0.086)	(0.028)	(0.041)
Betweenness centr. (dest)	0.317***	0.334***	0.261***	0.215***
	(0.053)	(0.093)	(0.029)	(0.043)
Technological proximity	1.108***	1.554***	1.239***	1.384***
	(0.234)	(0.476)	(0.090)	(0.137)
Same country	2.332***	2.252***	2.519***	2.536***
	(0.114)	(0.167)	(0.036)	(0.050)
Constant	−12.149***	−11.859***	−13.007***	−13.026***
	(0.454)	(0.640)	(0.246)	(0.354)
Adjusted Moran's I	0.343***	0.352***	0.076***	0.082***
Log likelihood/disp.	−21972.08	−35409.02	−10298.94	−16466.88
Number of eigenvectors			61	61
Observations	246 512	246 512	246 512	246 512

Standard errors are robust. The adjusted Moran's I uses $n^2 \times n^2$ spatial weight matrix computed as $W_2 = W \otimes W$ where W is specified using driving distance-based neighbours with a 150km cut-off distance. After the two-step selection procedure described above, $Q = 61$ eigenvectors are selected to build the spatial filters at origin and destination. For the goodness-of-fit measure, the model is fitted twice, once with a regular likelihood Poisson model and once with the quasi variant model. The log-likelihood is extracted from the former and the dispersion parameter from the latter.

Gravity variables

In line with the theory behind the gravity equation, the results confirms that size and distance are important determinant of inventors' mobility. Specifically, the coefficient associated with the stock of inventors remain strongly positive and significant over the two periods, with estimated elasticities between 0.5 and 0.6. Coefficients associated with the origin are larger than those linked to the destination, because the former measures the ability of cities to generate flows. Looking at driving distance in particular, the estimated coefficients are negative and significant, which suggest that the pecuniary and non-pecuniary costs associated with moving significantly impede inventors' mobility. The importance of distance is greatly reduced when we introduce other variables that have a spatial dimension. This is because geographical distance serves as a proxy for other, more meaningful forms of distance. This being said, the importance of distance may be overestimated if other meaningful forms of proximity are not controlled for. Table 10 presented in the annex compares various forms of distance using the preferred specification for the period 2000-2003. The results show that using geographical distance rather than driving distance does not change the estimates. Consistently with Breschi and Lenzi (2010), distance does not affect mobility in a linear fashion, the inclusion of a squared distance variable reveals that the cost of moving is high but strongly decreases as we move further away.

Variables of interest

Turning to the variables of interest, both the labour market and the network variables have the expected sign and remain significant over the two periods. Considering employment opportunities in particular, the two variables introduced jointly in the regression are fairly similar in magnitude, with estimated elasticities around 0.6. Point estimates tend to be lower in the second period for the non-spatial model. This difference may be attributed to the smaller number of moves during this period than during the first one[14], which cause the mobility variable to be imperfectly observed. Overall, the evidence shows that employment opportunities strongly influence the mobility decisions of inventors. This results are in line with those reported by Miguelez and Moreno (2014) at the level of European regions, and provide additional robustness due to the explicit modelling of spatial autocorrelation, and the analysis at the urban scale.

Looking at the network variables in particular, both direct social ties and the centrality index are strongly positive and significant. This confirms, in a European context, that collaboration networks play an important role in matching workers to positions (Nakajima et al., 2010), because

[14] 4608 moves took place during the first period while only 1422 occurred during the second. This is because the database contains just a few observations for 2007 and 2008. This problem is magnified by the way mobility is computed, since I assume that a move took place between the application dates of the two patents, provided that there is no more than a four-year lag between the two. For instance, mobility in 2007 only include moves for which both patents were applied for in 2007 and moves for which patents the first patent was applied for in 2006 and the second in 2008.

it reduces information asymmetries and improve matching (Jackson, 2011). The elasticities associated with direct collaborations are similar to the estimates on labour market variables, which suggests that inventors' mobility is driven by both social ties, and employment opportunities in similar proportions. Comparing the two network variables, direct social ties matter more than the centrality index. This is not surprising given that the former measures direct social connections between inventors, which is more likely to influence the decision to move. Nonetheless, the fact that the two variables remain significant when introduced jointly in the regression suggests that the importance of inventors' networks goes beyond the effect of direct collaborations. The relative position of the city within the network, which represent a less restrictive definition of networks, is also important. Finally, spatial filtering reduces the importance of both network variables, since the social context in which inventors are embedded has a strong spatial dimension.

Control variables

The coefficients associated with the technological proximity index and the same country indicator variable are strongly positive and significant. The latter result is in line with the descriptive analysis, which shows that inventors' mobility in Europe is largely a national phenomenon. One possible explanation is the large amount of intra-firm and circular mobility. However, the limited availability of information about the assignee at origin and destination does not allow a more formal analysis. Nonetheless, this result suggests that the diversity of cultures and the fragmentation of institutional frameworks in the European Union may severely reduce the mobility of inventors. This may be one reason why skilled mobility in Europe is lower than in the United States. Bear in mind that the indicator variable is arguably a rather simple proxy to capture elements as diverse as culture, institutions or language. Finally, technological proximity is an important determinant of inventors' mobility. As shown in the descriptive analysis, inventors' tend to be specialised in a single technological sector. As such, they may not have many alternative destinations to choose from, in the sense that they can benefit from employment opportunities only in those cities with a similar technological specialisation. Similarly, co-invention networks are primarily developed between inventors belonging to same technological field. To the extent that these networks influence mobility decisions, this should increase again the probability to observe a move between technologically proximate cities.

6 Conclusion

Highly skilled professionals are regarded as one of the main driver for the economic development of cities through their effect on innovative capabilities. Skilled individuals are mobile in space and tend to cluster within a limited number of urban areas, therefore a crucial question is what factors shape this flows and influence the divergent levels of economic development across urban areas. Building on these considerations, this paper takes advantage of a large-scale dataset to shed light on the patterns and determinants of inventors' mobility across European urban areas. First, a descriptive analysis is carried out to document the dynamics of inventors' mobility and their spatial dimension. Second, a gravity model is used to analyse how job opportunities and socio-professional networks influence the flows of inventors between urban areas. From a methodological perspective, this paper uses a spatial filtering variant of the Poisson gravity model, which accommodate the nature of the data, while controlling for multilateral resistance and spatial autocorrelation in mobility flows.

Despite the commonly held belief that skilled workers are highly mobile in space, the analysis suggests that mobility remains a rare event. Among multi-patenting inventors, only 9.67% moved from one city to another between 1975 and 2008. Mobility is also limited in space; inventors who move travel between relatively large and co-located urban areas, and 90% of these moves occur within the same country. These results can be partly explained by the high level of circular and intra-firm mobility. Finally, the analysis highlight significant heterogeneity among countries, with about 80% of all moves taking place either in Germany, France or the UK. Likewise, the propensity to move vary importantly across technological sectors. Turning to the determinants of inventors' mobility, four results are worth noting. First, inventors are drawn toward cities offering numerous employment opportunities along with attractive working conditions. This finding is in line with the scarce existing evidence, provided by Miguelez and Moreno (2014) at the level of European regions, yet the explicit modelling of spatial autocorrelation and the analysis at the urban scale provide additional robustness to this finding. Second, the decision to move is mediated by network ties, which reduce information asymmetries between inventors and their potential employers, and therefore improve matching (Jackson, 2011). Besides, the definition of networks should not be restricted to direct collaborations. In particular, the centrality of cities, which represent a less restricted view of social networks, also plays a role. Third, contrary to expectations, geographical distance has a limited role in deterring mobility. This may be due to the availability of fast transportation across cities and because it acts as a proxy for other, more meaningful forms of distance. In particular, mobility occurs primarily between cities sharing the same technological specialisation, partly because of the availability of specialised jobs, partly because collaboration networks tend to develop within the same epistemic community. More importantly, cultural and institutional distance translate into greater adaptation costs. Fourth, from a methodological perspective, spatial autocorrelation in mobility flows is a serious issue and should be explicitly controlled for when estimating the gravity model in order to obtain unbiased parameter estimates.

These results have implications for the geography of innovation. While both mobility and networks have been shown to influence the diffusion of knowledge, they have often been investigated separately, and it would be interesting to study the interrelation between these two channels, as they appear to be closely related. Another implication concerns the ongoing construction of the European Research Area, which aims to facilitate the diffusion of local and external knowledge, in particular through the mobility of skilled individuals. The results suggest that the diffusion of knowledge may be limited for several reasons. Movers, represent only a fraction of the inventors; and those who move travel relatively short distances, generally within the same country. This result is magnified by the fact that a large portion of mobility occur within firms, and cannot be associated with a transfer of knowledge. Besides, the fact that mobility occurs primarily between technologically related cities may cause the transferred knowledge to be redundant, and have a limited economic impact. Finally, the results highlight significant heterogeneity across cities, and countries. A more promising finding is that mobility may be encouraged, in particular through the development of research collaborations involving distant research communities.

Further research on other categories of skilled workers would be welcome, as inventors represent only a fraction of the skilled workforce. As noted by Mahroum (2000), skilled mobility is a diverse phenomenon and what may be true for inventors does not necessarily hold for other categories of skilled workers. However, the study of mobility is often made impossible by the lack of harmonized and reliable data. Finally, the empirical analysis is fairly macroeconomic and do not consider the influence of personal characteristics such as age, gender, tenure or productivity on the mobility patterns of inventors as in Crespi et al. (2007) and Lenzi (2009).

References

Agrawal, Ajay , Cockburn, Iain , and McHale, John . Gone but not forgotten: Knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography*, 6(5):571–591, 2006.

Almeida, Paul and Kogut, Bruce . Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, 45(7):905–917, 1999.

Anderson, James E. and van Wincoop, Eric . Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, 93(1):170–192, 2003.

Audretsch, David B. and Feldman, Maryann P. . Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, 43(2):409–429, 1999.

Baldwin, Richard E. and Forslid, Rikard . The core-periphery model and endogenous growth: Stabilizing and destabilizing integration. *Economica*, 67(267):307–324, 2000.

Beenstock, Michael and Felsenstein, Daniel . Spatial dependence in the eonometrics of gravity modeling. 2013.

Behrens, Kristian , Ertur, Cem , and Koch, Wilfried . Dual gravity: Using spatial econometrics to control for multilateral resistance. *Journal of Applied Econometrics*, 27(5):773–794, 2012.

Berge, Laurent R. , Wanzenbock, Iris , and Scherngell, Thomas . Centrality of regions in R&D networks: A new measurement approach using the concept of bridging paths. 2015.

Berry, Christopher R. and Glaeser, Edward L. . The divergence of human capital levels across cities. *Regional Science*, 84(3):407–444, 2005.

Bertoli, Simone and Moraga, Jesus Fernandez-Huertas . Multilateral resistance to migration. *Journal of Development Economics*, 102:79–100, May 2013.

Bettencourt, Luis M. A. , Lobo, Jose , and Strumsky, Deborah . Invention in the city: Increasing returns to patenting as a scaling function of metropolitan size. *Research Policy*, 36(1):107–120, 2007.

Black, Duncan and Henderson, Vernon . A theory of urban growth. *Journal of Political Economy*, 107(2):252–284, 1999.

Breschi, Stefano and Lenzi, Camilla . Spatial patterns of inventors' mobility: Evidence on US urban areas. *Papers in Regional Science*, 89(2):235–250, 2010.

Carlino, Gerald A. , Chatterjee, Satyajit , and Hunt, Robert M. . Urban density and the rate of invention. *Journal of Urban Economics*, 61(3):389–419, 2007.

Chun, Yongwan . Modeling network autocorrelation within migration flows by eigenvector spatial filtering. *Journal of Geographical Systems*, 10(4):317–344, 2008.

Chun, Yongwan and Griffith, Daniel A. . Modeling network autocorrelation in space-time migration flow data: An eigenvector spatial filtering approach. *Annals of the Association of American Geographers*, 101(3):523–536, 2011.

Crespi, Gustavo , Geuna, Aldo , and Nesta, Lionel . The mobility of university inventors in europe. *The Journal of Technology Transfer*, 32(3):195–215, 2007.

Dahl, Michael S. Dahl and Sorenson, Olav . The migration of technical workers. *Journal of Urban Economics*, 67(1):33–45, 2010.

Djikstra, Lewis and Poelman, Hugo . Cities in europe, the new OECD-EC definition. Technical report, European Commission, 2012.

Dorfman, Jeffrey H. , Partridge, Mark D. , and Galloway, Hamilton . Do natural amenities attract high-tech jobs? evidence from a smoothed bayesian spatial model. *Spatial Economic Analysis*, 6(4):397–422, 2011.

Faggian, Alessandra and McCann, Philip . Human capital flows and regional knowledge assets: A simultaneous equation approach. *Oxford Economic Papers*, 58(3):475–500, 2006.

Faggian, Alessandra and McCann, Philip . Human capital, graduate migration and innovation in british regions. *Cambridge Journal of Economics*, 33(2):317–333, 2009.

Fischer, Manfred M. and Griffith, Daniel A. . Modeling spatial autocorrelation in spatial interaction data: An application to patent citation data in the european union. *Journal of Regional Science*, 45(5):969–989, 2008.

Florida, Richard . The economic geography of talent. *Annals of the Association of American Geographers*, 92(4):743–755, 2002.

Fujita, Masahisa and Thisse, Jacques-Francois . On the relationship between agglomeration and growth. In Fujita, Masahisa and Thisse, Jacques-Francois , editors, *Economics of Agglomeration*, chapter 11, pages 388–459. Cambridge University Press, 2002.

Glaeser, Edward L. . Learning in cities. *Journal of Urban Economics*, 46(2):254–277, September 1999.

Glaeser, Edward L and Resseger, Matthew G. . The complementarity between cities and skills. *Journal of Regional Science*, 50(1):221–244, 2010.

Glaeser, EL , Saiz, A , Burtless, G , and Strange, WC . The rise of the skilled city. *Brookings-Wharton Papers on Urban Affairs*, pages 47–105, 2004. ISSN 15287084.

Gourieroux, Christian , Monfort, Alain , and Trognon, Alain . Pseudo-maximum likelihood methods: Applications to poisson models. *Econometrica*, 52(3):701–720, 1984.

Graves, Philip E. . Migration and climate. *Journal of Regional Science*, 16(1):107–112, 1980.

Griffith, DA . *Spatial autocorrelation and spatial filtering: Gaining understanding through theory and scientific visualization.* Springer, Berlin Heidelberg New York, 2003.

Griffith, Daniel A. . Modeling spatial autocorrelation in spatial interaction data: Empirical evidence from 2002 germany journey-to-work flows. *Journal of Geographical Systems*, 11(2):117–140, 2009.

Grossman, Gene M and Helpman, Elhanan . *Innovation and growth in the world economy.* The MIT Press, 1991.

Hoisl, Karin . Tracing mobile inventors: The causality between inventor mobility and inventor productivity. *Research Policy*, 36(5):619–636, 2007.

Jackson, Matthew O. . An overview of social networks and economic applications. In Benhabib, Jess , Bisin, Alberto , and Jackson, Matthew O. , editors, *Handbook of Social Economics*, volume 1, chapter 12, pages 511–585. North-Holland, 2011.

Jacobs, Jane . *The economy of cities.* Vintage Books, New York, 1969.

Jaffe, Adam B. . Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *The American Economic Review*, 76(5):984–1001, 1986.

Jaffe, Adam B. , Trajtenberg, Manuel , and Henderson, Rebecca . Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, 108 (3):577–98, 1993.

Koch, Wilfried and LeSage, James P. . Latent multilateral trade resistance indices: Theory and evidence. *Scottish Journal of Political Economy*, 62(3):264–290, 2015.

Krabel, Stefan and Flother, Choni . Here today, gone tomorrow? Regional labour mobility of german university graduates. *Regional Studies*, 48(10):1609–1627, 2014.

Krisztin, Tamas and Fischer, Manfred M. . The gravity model for international trade: Specification and estimation issues. *Spatial Economic Analysis*, 10(4):451–470, 2015.

Krugman, Paul . Increasing returns and economic geography. *Journal of Political Economy*, 99 (3):483–99, 1991.

Lai, Ronald , Doolin, David M. , Li, Guan-Cheng , Sum, Ye , Torvik, Vetle , Yu, Amy , and Fleming, Lee . Disambiguation and co-authorship networks of the US patent inventor database (1975-2010). Technical report, Harvard Dataverse, 2013.

Lenzi, Camilla . Patterns and determinants of skilled workers' mobility: Evidence from a survey of italian inventors. *Economics of Innovation and New Technology*, 18(2):161–179, 2009.

LeSage, James P. and Pace, Robert Kelley . The biggest myth in spatial econometrics. *Econometrics*, 2(4):217–249, 2014.

Lin, Ge and Zhang, Tonglin . Loglinear residual tests of Moran's I autocorrelation and their applications to kentucky breast cancer data. *Geographical Analysis*, 39(3):293–310, 2007.

Lucas, Robert Jr. . On the mechanics of economic development. *Journal of Monetary Economics*, 22(1):3–42, 1988.

Luxen, Dennis and Vetter, Christian . Real-time routing with openstreetmap data. In *Proceedings of the 19th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 513–516, 2011.

Mahroum, Sami . Highly skilled globetrotters: Mapping the international migration of human capital. *R&D Management*, 30(1):23–32, 2000.

Massard, Nadine and Mehier, Caroline . Proximity and innovation through an 'accessibility to knowledge' lens. *Regional Studies*, 43(1):77–88, 2009.

Miguelez, Ernest . How does geographical mobility of inventors influence network formation? Economic Research Working Papers 07, World Intellectual Property Organization, 2013.

Miguelez, Ernest and Moreno, Rosina . What attracts knowledge workers? The role of space and social networks. *Journal of Regional Science*, 54(1):33–60, 2014.

Nakajima, Ryo , Tamura, Ryuichi , and Hanaki, Nobuyuki . The effect of collaboration network on inventors' job match, productivity and tenure. *Labour Economics*, 17(4):723–734, 2010.

Nifo, Annamaria and Vecchione, Gaetano . Do institutions play a role in skilled migration? The case of italy. *Regional Studies*, 48(10):1628–1649, 2014.

Patuelli, Roberto , Griffith, Daniel A. , Tiefelsdorf, Michael , and Nijkamp, Peter . Spatial filtering and eigenvector stability: Space-time models for german unemployment data. *International Regional Science Review*, 32(2):253–280, 2011.

Patuelli, Roberto , Linders, Gert-Jan , Metulini, Rudolfo , and Griffith, Daniel A. . The space of gravity: Spatial filtering estimation of a gravity model for bilateral trade. 2015.

Romer, Paul Michael . Endogenous technological change. *Journal of Political Economy*, 98(5): 71–102, 1990.

Santos Silva, Joao M.C. and Tenreyro, Silvana . The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658, 2006.

Scherngell, Thomas and Lata, Rafael . Towards an integrated european research area? findings from eigenvector spatially filtered spatial interaction models using european framework programme data. *Papers in Regional Science*, 92(3):555–577, 2013.

Scott, Allen J. . Jobs or amenities? Destination choices of migrant engineers in the usa. *Papers in Regional Science*, 89(1):43–63, 2010.

Shapiro. Smart cities: Quality of life, productivity, and the growth effects of human capital. *The Review of Economics and Statistics*, 88(2):324–335, 2006.

Tiefelsdorf, Michael and Griffiths, Daniel A. . Semiparametric filtering of spatial autocorrelation: The eigenvector approach. *Environment and Planning*, 39(5):1193–1221, 2007.

Annex

Table 9: Cross-sectional estimation results, excluding Germany, 2000-2003

	Spatially filtered Quasi-Poisson
Stock of inventors (orig)	0.610^{***}
	(0.019)
Stock of inventors (dest)	0.516^{***}
	(0.026)
Driving distance	-0.367^{***}
	(0.025)
R&D expenditures (dest)	0.652^{***}
	(0.047)
Human res. in S&T (dest)	0.716^{***}
	(0.039)
Collaborations count	0.665^{***}
	(0.019)
Betweenness centr. (orig)	0.274^{***}
	(0.057)
Betweenness centr. (dest)	0.286^{***}
	(0.061)
Technological proximity	1.085^{***}
	(0.134)
Same country	2.468^{***}
	(0.060)
Constant	-12.707^{***}
	(0.465)
Number of eigenvectors	33
Observations	174 306

Table 10: Cross-sectional estimation results comparing various forms of distance, 2000-2003

	Spatially filtered Quasi Poisson			
	Driving distance (1)	Geographical distance (2)	Squared driving dist. (3)	Distance only (4)
Stock of inventors (orig)	0.634*** (0.014)	0.641*** (0.014)	0.625*** (0.014)	0.912*** (0.013)
Stock of inventors (dest)	0.556*** (0.017)	0.563*** (0.017)	0.553*** (0.017)	0.884*** (0.013)
Driving distance	−0.312*** (0.018)		−19.495*** (2.882)	−1.580*** (0.019)
Geographical distance		−0.288*** (0.017)		
Driving distance^2			9.514*** (1.429)	
R&D expenditures (dest)	0.649*** (0.031)	0.645*** (0.031)	0.651*** (0.031)	
Human res. in S&T (dest)	0.699*** (0.027)	0.696*** (0.027)	0.697*** (0.027)	
Collaborations count	0.649*** (0.010)	0.644*** (0.010)	0.665*** (0.010)	
Betweenness centr. (orig)	0.278*** (0.028)	0.280*** (0.028)	0.276*** (0.028)	
Betweenness centr. (dest)	0.261*** (0.029)	0.265*** (0.029)	0.254*** (0.029)	
Technological proximity	1.239*** (0.090)	1.237*** (0.090)	1.229*** (0.089)	
Same country	2.519*** (0.036)	2.544*** (0.036)	2.419*** (0.039)	
Constant	−13.007*** (0.246)	−13.188*** (0.241)	−11.851*** (0.299)	−2.599*** (0.143)
Number of eigenvectors	61	61	61	61
Observations	246 512	246 512	246 512	246 512

Table 11: Technological classes and subclasses

Categories	Subcategories
1 chemical	11 agriculture, food, textiles
	12 coating
	13 gas
	14 resins
	14 organic compounds
	15 resins
	19 miscellaneous
2 computers, communica- -tions	21 communications
	22 computer hardware, software
	23 computer peripherials
	24 information storage
	25 electronic business methods and software
	29 miscellaneous
3 drugs, medical	31 drugs
	32 surgery, medical instruments
	33 genetics
	39 miscellaneous
4 electrical, electronic	41 electrical devices
	42 electrical lighting
	43 measuring, testing
	44 nuclear, x-rays
	45 power systems
	46 semiconductor devices
	49 miscellaneous
5 mechanical	51 mat. proc, handling
	52 metal working
	53 motors, engines, parts
	54 optics
	55 transportation
	59 miscellaneous
6 others	61 agriculture, husbandry, food
	62 amusement devices
	63 apparel, textile
	64 earth working, wells
	65 furniture, house fixtures
	66 heating
	67 pipes, joints
	68 receptacles
	69 miscellaneous

Source: NBER Patent Data Project

Countries	Larger Urban Zones (LUZ)
Austria (AT)	Wien (AT001L2), Graz (AT002L2), Linz (AT003L2), Salzburg (AT004L2), Innsbruck (AT005L2), Klagenfurt (AT006L1)
Belgium (BE)	Bruxelles (BE001L2), Antwerpen (BE002L2), Gent (BE003L2), Charleroi (BE004L2), Liege (BE005L2), Brugge (BE006L2), Namur (BE007L2), Leuven (BE008L1), Mons (BE009L1), Kortrijk (BE010L1), Oostende (BE011L1)
Bulgaria (BG)	Sofia (BG001L2), Plovdiv (BG002L2), Varna (BG003L2), Burgas (BG004L2), Pleven (BG005L1), Ruse (BG006L2), Vidin (BG007L2), Stara Zagora (BG008L2), Sliven (BG009L1), Plovdiv (BG010L1), Shumen (BG011L1), Yambol (BG013L1), Haskovo (BG014L1), Pazardzhik (BG015L1), Blagoevgrad (BG016L1), Veliko Tarnovo (BG017L1), Vratsa (BG018L1)
Switzerland (CH)	Zurich (CH001L1), Geneve (CH002L1), Basel (CH003L1), Bern (CH004L1), Lausanne (CH005L1), Winterthur (CH006L1), St Gallen (CH007L1), Luzern (CH008L1), Lugano (CH009L2), Biel (CH010L1)
Czech Republic (CZ)	Praha (CZ001L1), Brno (CZ002L1), Ostrava (CZ003L1), Plzen (CZ004L1), Usti Nad Labem (CZ005L1), Olomouc (CZ006L1), Liberec (CZ007L1), Ceske Budejovice (CZ008L1), Hradec Kralove (CZ009L1), Pardubice (CZ010L1), Zlin (CZ011L1), Karlovy Vary (CZ013L1), Jihlava (CZ014L1), Most (CZ016L1), Chomutov (CZ018L1)

Germany (DE)	Berlin (DE001L1), Hamburg (DE002L1), Munchen (DE003L1), Koln (DE004L1), Frankfurt Am Main (DE005L1), Stuttgart (DE007L1), Leipzig (DE008L2), Dresden (DE009L2), Dusseldorf (DE011L1), Bremen (DE012L1), Hannover (DE013L1), Nurnberg (DE014L1), Bielefeld (DE017L0), Halle An Der Saale (DE018L1), Magdeburg (DE019L2), Wiesbaden (DE020L1), Gottingen (DE021L1), Darmstadt (DE025L1), Trier (DE026L1), Freiburg Im Breisgau (DE027L1), Regensburg (DE028L1), Frankfurt (DE029L0), Weimar (DE030L1), Schwerin (DE031L1), Erfurt (DE032L1), Augsburg (DE033L1), Bonn (DE034L1), Karlsruhe (DE035L1), Monchengladbach (DE036L0), Mainz (DE037L1), Ruhrgebiet (DE038L1), Kiel (DE039L1), Saarbrucken (DE040L1), Koblenz (DE042L1), Rostock (DE043L2), Kaiserslautern (DE044L1), Iserlohn (DE045L1), Wilhelmshaven (DE048L1), Tubingen (DE050L1), Villingen Schwenningen (DE051L1), Flensburg (DE052L1), Marburg (DE053L1), Konstanz (DE054L1), Neumunster (DE055L0), Brandenburg An Der Havel (DE056L0), Giessen (DE057L1), Luneburg (DE058L1), Bayreuth (DE059L1), Celle (DE060L1), Aschaffenburg (DE061L1), Bamberg (DE062L1), Plauen (DE063L1), Neubrandenburg (DE064L1), Fulda (DE065L1), Kempten (DE066L1), Landshut (DE067L1), Rosenheim (DE069L1), Stralsund (DE071L1), Friedrichshafen (DE072L1), Offenburg (DE073L1), Gorlitz (DE074L1), Schweinfurt (DE077L1), Greifswald (DE078L1), Wetzlar (DE079L1), Passau (DE081L1), Dessau Rosslau (DE082L0), Braunschweig Salzgitter Wolfsburg (DE083L1), Mannheim Ludwigshafen (DE084L1), Munster (DE504L1), Chemnitz (DE505L0), Aachen (DE507L1), Krefeld (DE508L0), Lubeck (DE510L1), Kassel (DE513L1), Solingen (DE516L0), Osnabruck (DE517L1), Oldenburg (DE520L1), Heidelberg (DE522L1), Paderborn (DE523L1), Wurzburg (DE524L2), Bremerhaven (DE527L1), Heilbronn (DE529L1), Remscheid (DE530L0), Ulm (DE532L1), Pforzheim (DE533L1), Ingolstadt (DE534L1), Gera (DE535L1), Reutlingen (DE537L1), Cottbus (DE539L1), Siegen (DE540L2), Hildesheim (DE542L1), Zwickau (DE544L1), Wuppertal (DE546L0), Jena (DE547L2)
Denmark (DK)	Kobenhavn (DK001L2), Arhus (DK002L2), Odense (DK003L1), Aalborg (DK004L2)
Estonia (EE)	Tallinn (EE001L1), Tartu (EE002L1), Narva (EE003L0)
Greece (EL)	Athina (EL001L1), Thessaloniki (EL002L1), Patra (EL003L1), Irakleio (EL004L1), Larisa (EL005L1), Volos (EL006L1), Ioannina (EL007L1), Kavala (EL008L1), Kalamata (EL009L1)

Spain (ES)	Madrid (ES001L2), Barcelona (ES002L2), Valencia (ES003L2), Sevilla (ES004L2), Zaragoza (ES005L2), Malaga (ES006L2), Murcia (ES007L2), Valladolid (ES009L2), Palma De Mallorca (ES010L2), Santiago De Compostela (ES011L2), Vitoria (ES012L2), Oviedo (ES013L2), Pamplona (ES014L2), Santander (ES015L2), Toledo (ES016L2), Badajoz (ES017L2), Logrono (ES018L2), Bilbao (ES019L2), Cordoba (ES020L2), Alicante (ES021L2), Vigo (ES022L2), Gijon (ES023L2), Coruna (ES026L2), Reus (ES028L1), Lugo (ES031L0), Girona (ES033L0), Caceres (ES034L0), Torrevieja (ES035L0), Puerto De Santa Maria El (ES037L0), Aviles (ES039L0), Talavera De La Reina (ES040L0), Palencia (ES041L0), Ferrol (ES043L0), Pontevedra (ES044L0), Ceuta (ES045L0), Gandia (ES046L0), Guadalajara (ES048L0), Manresa (ES050L0), Ciudad Real (ES053L0), Benidorm (ES054L0), Melilla (ES055L0), Ponferrada (ES057L0), Zamora (ES059L0), Sanlucar De Barrameda (ES062L0), Linea De La Concepcion La (ES065L0), Irun (ES070L0), Elda (ES073L0), Granada (ES501L1), Elche (ES505L1), Cartagena (ES506L1), Jerez De La Frontera (ES508L1), Donostia San Sebastian (ES510L1), Almeria (ES514L1), Burgos (ES515L1), Salamanca (ES516L1), Albacete (ES519L1), Castellon De La Plana (ES520L1), Huelva (ES521L1), Cadiz (ES522L1), Leon (ES523L1), Tarragona (ES525L1), Jaen (ES527L1), Lleida (ES528L1), Ourense (ES529L1), Algeciras (ES532L1), Marbella (ES533L1)
Finland (FI)	Helsinki (FI001L2), Tampere (FI002L2), Turku (FI003L2), Oulu (FI004L2), Lahti (FI007L1), Kuopio (FI008L1), Jyvaskyla (FI009L1)

France (FR)	Paris (FR001L1), Lyon (FR003L2), Toulouse (FR004L2), Strasbourg (FR006L2), Bordeaux (FR007L2), Nantes (FR008L2), Lille (FR009L2), Montpellier (FR010L2), Saint Etienne (FR011L2), Le Havre (FR012L2), Rennes (FR013L2), Amiens (FR014L2), Nancy (FR016L2), Metz (FR017L2), Reims (FR018L2), Orleans (FR019L2), Dijon (FR020L2), Poitiers (FR021L2), Clermont Ferrand (FR022L2), Caen (FR023L2), Limoges (FR024L2), Besancon (FR025L2), Grenoble (FR026L2), Ajaccio (FR027L2), Toulon (FR032L2), Valenciennes (FR034L2), Tours (FR035L2), Angers (FR036L2), Brest (FR037L2), Le Mans (FR038L2), Avignon (FR039L1), Mulhouse (FR040L2), Dunkerque (FR042L2), Perpignan (FR043L2), Nimes (FR044L2), Pau (FR045L2), Bayonne (FR046L2), Annemasse (FR047L0), Annecy (FR048L2), Lorient (FR049L2), Montbelliard (FR050L2), Troyes (FR051L2), Saint Nazaire (FR052L2), La Rochelle (FR053L2), Angouleme (FR056L2), Boulogne Sur Mer (FR057L2), Chambery (FR058L2), Chalon Sur Saone (FR059L2), Chartres (FR060L2), Niort (FR061L2), Calais (FR062L2), Beziers (FR063L2), Arras (FR064L2), Bourges (FR065L2), Saint Brieuc (FR066L2), Quimper (FR067L2), Vannes (FR068L2), Cherbourg (FR069L2), Tarbes (FR073L2), Compiegne (FR074L2), Belfort (FR076L2), Roanne (FR077L2), Saint Quentin (FR079L2), Beauvais (FR082L2), Creil (FR084L2), Evreux (FR086L2), Chateauroux (FR090L2), Brive La Gaillarde (FR093L2), Albi (FR096L2), Frejus (FR099L2), Chalons En Champagne (FR104L2), Marseille (FR203L2), Nice (FR205L2), Lens Lievin (FR207L2), Henin Carvin (FR208L1), Douai (FR209L2), Valence (FR214L1), Rouen (FR215L2), Melun (FR304L1), Martigues (FR324L1), Charleville Mezieres (FR505L1), Colmar (FR506L1)
Croatia (HR)	Grad Zagreb (HR001L2), Rijeka (HR002L2), Slavonski Brod (HR003L2), Osijek (HR004L2), Split (HR005L2)
Hungary (HU)	Budapest (HU001L2), Miskolc (HU002L2), Nyiregyhaza (HU003L2), Pecs (HU004L2), Debrecen (HU005L2), Szeged (HU006L2), Gyor (HU007L2), Kecskemet (HU008L2), Szekesfehervar (HU009L2), Szombathely (HU010L1)
Ireland (IE)	Dublin (IE001L1), Cork (IE002L1), Limerick (IE003L1), Galway (IE004L1), Waterford (IE005L1)

Italy (IT)	Roma (IT001L2), Milano (IT002L2), Napoli (IT003L2), Torino (IT004L2), Palermo (IT005L2), Genova (IT006L2), Firenze (IT007L2), Bari (IT008L2), Bologna (IT009L1), Catania (IT010L2), Venezia (IT011L2), Verona (IT012L2), Cremona (IT013L2), Trento (IT014L2), Trieste (IT015L1), Perugia (IT016L2), Ancona (IT017L2), Pescara (IT019L2), Campobasso (IT020L2), Caserta (IT021L2), Taranto (IT022L2), Potenza (IT023L2), Catanzaro (IT024L2), Reggio Di Calabria (IT025L2), Sassari (IT026L2), Cagliari (IT027L1), Padova (IT028L2), Brescia (IT029L2), Modena (IT030L2), Foggia (IT031L2), Salerno (IT032L2), Piacenza (IT033L1), Bolzano (IT034L1), Udine (IT035L1), La Spezia (IT036L1), Lecce (IT037L1), Barletta (IT038L1), Pesaro (IT039L1), Como (IT040L1), Pisa (IT041L1), Treviso (IT042L1), Varese (IT043L1), Busto Arsizio (IT044L1), Asti (IT045L1), Pavia (IT046L1), Massa (IT047L1), Cosenza (IT048L1), Carrara (IT049L1), Benevento (IT050L1), Sanremo (IT051L1), Savona (IT052L1), Vigevano (IT053L1), Matera (IT054L1), Viareggio (IT055L1), Acireale (IT056L1), Avellino (IT057L1), Pordenone (IT058L1), Biella (IT059L1), Lecco (IT060L1), Messina (IT501L2), Prato (IT502L2), Parma (IT503L2), Livorno (IT504L2), Reggio Nell Emilia (IT505L2), Ravenna (IT506L2), Ferrara (IT507L2), Rimini (IT508L2), Siracusa (IT509L2), Bergamo (IT511L2), Forli (IT512L2), Latina (IT513L2), Vicenza (IT514L2), Terni (IT515L2), Novara (IT516L2)
Lithuania (LT)	Vilnius (LT001L1), Kaunas (LT002L1), Panevezys (LT003L1), Alytus (LT004L0), Klaipeda (LT501L0), Siaulai (LT502L0)
Luxembourg (LU)	Luxembourg (LU001L1)
Latvia (LV)	Riga (LV001L0), Liepaja (LV002L1), Jelgava (LV003L1), Daugavpils (LV501L1)
Malta (MT)	Valletta (MT001L1)
Netherlands (NL)	S Gravenhage (NL001L2), Amsterdam (NL002L2), Rotterdam (NL003L2), Utrecht (NL004L2), Eindhoven (NL005L2), Tilburg (NL006L2), Groningen (NL007L2), Enschede (NL008L2), Arnhem (NL009L2), Heerlen (NL010L2), Breda (NL012L2), Nijmegen (NL013L2), Apeldoorn (NL014L2), Leeuwarden (NL015L2), Sittard Geleen (NL016L1), Delft (NL017L1), Hilversum (NL018L1), Roosendaal (NL020L1), Alphen Aan Den Rijn (NL026L1), Bergen Op Zoom (NL028L1), Katwijk (NL029L1), Gouda (NL030L1), Middelburg (NL032L1), S Hertogenbosch (NL503L2), Amersfoort (NL504L2), Maastricht (NL505L1), Dordrecht (NL506L2), Leiden (NL507L2), Zwolle (NL511L2), Ede (NL512L1), Deventer (NL513L2), Alkmaar (NL514L2), Venlo (NL515L2), Almelo (NL519L2)
Norway (NO)	Oslo (NO001L1), Bergen (NO002L1), Trondheim (NO003L1), Stavanger (NO004L1), Kristiansand (NO005L1)

Poland (PL)	Warszawa (PL001L2), Lodz (PL002L2), Krakow (PL003L2), Wroclaw (PL004L2), Poznan (PL005L2), Gdansk (PL006L2), Szczecin (PL007L2), Bydgoszcz (PL008L2), Lublin (PL009L2), Katowice (PL010L2), Bialystok (PL011L2), Kielce (PL012L2), Torun (PL013L2), Olsztyn (PL014L2), Rzeszow (PL015L2), Opole (PL016L2), Gorzow Wielkopolski (PL017L2), Zielona Gora (PL018L2), Jelenia Gora (PL019L2), Nowy Sacz (PL020L2), Suwalki (PL021L2), Konin (PL022L2), Czestochowa (PL024L2), Radom (PL025L2), Plock (PL026L2), Kalisz (PL027L2), Koszalin (PL028L2), Slupsk (PL029L1), Jastrzebie Zdroj (PL030L1), Siedlce (PL031L1), Piotrkow Trybunalski (PL032L1), Lubin (PL033L1), Pila (PL034L1), Inowroclaw (PL035L1), Ostrowiec Swietokrzyski (PL036L1), Gniezno (PL037L1), Stargard Szczecinski (PL038L1), Ostrow Wielkopolski (PL039L1), Przemysl (PL040L1), Zamosc (PL041L1), Chelm (PL042L1), Pabianice (PL043L1), Glogow (PL044L1), Stalowa Wola (PL045L1), Tomaszow Mazowiecki (PL046L1), Lomza (PL047L1), Leszno (PL048L1), Swidnica (PL049L1), Tczew (PL051L1), Elk (PL052L1), Bielsko Biala (PL506L2), Rybnik (PL508L1), Walbrzych (PL511L2), Elblag (PL512L2), Wloclawek (PL513L2), Tarnow (PL514L2), Legnica (PL516L2), Grudziadz (PL517L2)
Portugal (PT)	Lisboa (PT001L2), Porto (PT002L2), Braga (PT003L1), Coimbra (PT005L2), Setubal (PT006L0), Aveiro (PT008L2), Faro (PT009L1), Viseu (PT014L0), Viana Do Castelo (PT016L0), Povoa De Varzim (PT019L0), Guimaraes (PT505L1)
Romania (RO)	Bucuresti (RO001L1), Cluj Napoca (RO002L1), Timisoara (RO003L1), Craiova (RO004L1), Braila (RO005L1), Oradea (RO006L1), Bacau (RO007L1), Arad (RO008L1), Sibiu (RO009L1), Targu Mures (RO010L1), Piatra Neamt (RO011L1), Calarasi (RO012L1), Giurgiu (RO013L1), Alba Iulia (RO014L1), Focsani (RO015L1), Targu Jiu (RO016L1), Tulcea (RO017L1), Targoviste (RO018L1), Slatina (RO019L1), Barlad (RO020L1), Roman (RO021L1), Bistrita (RO022L1), Constanta (RO501L1), Iasi (RO502L1), Galati (RO503L1), Brasov (RO504L1), Ploiesti (RO505L1), Pitesti (RO506L1), Baia Mare (RO507L1), Buzau (RO508L1), Satu Mare (RO509L1), Botosani (RO510L1), Ramnicu Valcea (RO511L1), Suceava (RO512L1), Drobeta Turnu Severin (RO513L1)
Sweden (SE)	Stockholm (SE001L1), Goteborg (SE002L1), Malmo (SE003L1), Jonkoping (SE004L1), Umea (SE005L1), Uppsala (SE006L1), Linkoping (SE007L1), Orebro (SE008L1), Vasteras (SE501L1), Norrkoping (SE502L1), Helsingborg (SE503L1), Boras (SE505L1)
Slovenia (SI)	Ljubljana (SI001L1), Maribor (SI002L1)
Slovakia (SK)	Bratislava (SK001L1), Kosice (SK002L1), Banska Bystrica (SK003L1), Nitra (SK004L1), Presov (SK005L1), Zilina (SK006L1), Trnava (SK007L1), Trencin (SK008L1)

The United Kingdom (UK)	London (UK001L2), West Midlands Urban Area (UK002L2), Leeds (UK003L1), Glasgow (UK004L1), Bradford (UK005L0), Liverpool (UK006L2), Edinburgh (UK007L1), Manchester (UK008L2), Cardiff (UK009L1), Sheffield (UK010L2), Bristol (UK011L2), Belfast (UK012L1), Newcastle Upon Tyne (UK013L2), Leicester (UK014L1), Derry (UK015L0), Aberdeen (UK016L1), Cambridge (UK017L1), Exeter (UK018L2), Lincoln (UK019L2), Stevenage (UK021L0), Wrexham (UK022L0), Portsmouth (UK023L1), Worcester (UK024L0), Coventry (UK025L2), Kingston Upon Hull (UK026L1), Stoke On Trent (UK027L1), Nottingham (UK029L1), Bath And North East Somerset (UK031L0), Guildford (UK033L0), Thanet (UK034L0), Waveney (UK038L0), Tunbridge Wells (UK040L0), Ashford (UK041L0), East Staffordshire (UK043L0), Darlington (UK044L0), Worthing (UK045L0), Mansfield (UK046L0), Chesterfield (UK047L0), Burnley (UK050L1), Great Yarmouth (UK051L0), Hartlepool (UK053L0), Cannock Chase (UK054L0), Eastbourne (UK055L0), Hastings (UK056L1), Redditch (UK059L0), Kirklees (UK501L0), Doncaster (UK506L0), Sunderland (UK510L0), Medway (UK513L0), Brighton And Hove (UK515L1), Plymouth (UK516L0), Swansea (UK517L1), Derby (UK518L1), Barnsley (UK519L0), Southampton (UK520L1), Milton Keynes (UK525L0), Northampton (UK528L0), Warrington (UK531L0), Luton (UK532L0), York (UK533L0), Swindon (UK535L0), Bournemouth (UK539L1), Wycombe (UK540L0), Telford And Wrekin (UK542L0), North East Lincolnshire (UK543L0), Peterborough (UK545L0), Colchester (UK546L0), Basingstoke And Deane (UK548L0), Bedford (UK549L0), Dundee City (UK550L0), Falkirk (UK551L0), Reading (UK552L0), Blackpool (UK553L1), Maidstone (UK554L0), Dacorum (UK556L0), Blackburn With Darwen (UK557L1), Newport (UK558L1), Middlesbrough (UK559L1), Oxford (UK560L0), Torbay (UK561L0), Preston (UK562L1), Warwick (UK564L0), Norwich (UK566L1), Cheshire West And Chester (UK568L1), Ipswich (UK569L1), Cheltenham (UK571L1), Gloucester (UK572L0), Bracknell Forest (UK573L0), Carlisle (UK575L0), Crawley (UK576L0)